CS5760: Computer Vision

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Lecture 9: RANSAC

http://www.wired.com/gadgetlab/2010/07/camera-software-lets-you-see-into-the-past/

Reading

- Szeliski: Chapter 6.1

Announcements

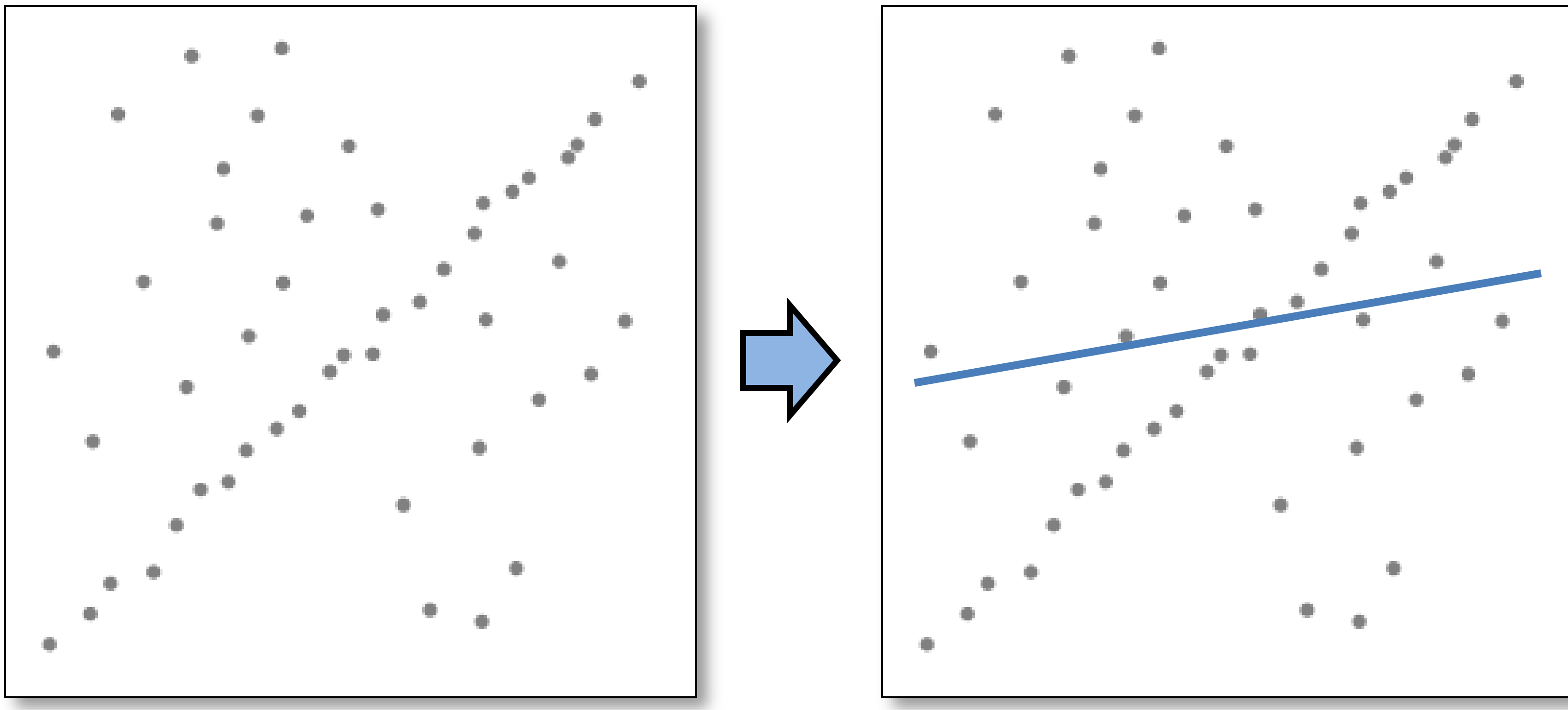
- Project 2 – code due today at 11:59pm
  - Report due Friday at 11:59pm
- Midterm
  - Plan to release in class next Wednesday, 3/13
  - Due at the beginning of class, Monday, 3/18
- Kristen Grauman talk
  - Friday at noon

Outliers

outliers
MAKING
COMICS
STORYTELLING SECRETS OF COMICS, MANGA, AND GRAPHIC NOVELS
FROM THE AUTHOR OF UNDERSTANDING COMICS
SCOTT McCLOUD
SOUTH WEST
The Complete
BLACK ADDER
BBC
inliers

Robustness

- Let's consider a simpler example… linear regression



Problem: Fit a line to these datapoints

Least squares fit

- How can we fix this?

We need a better cost function…

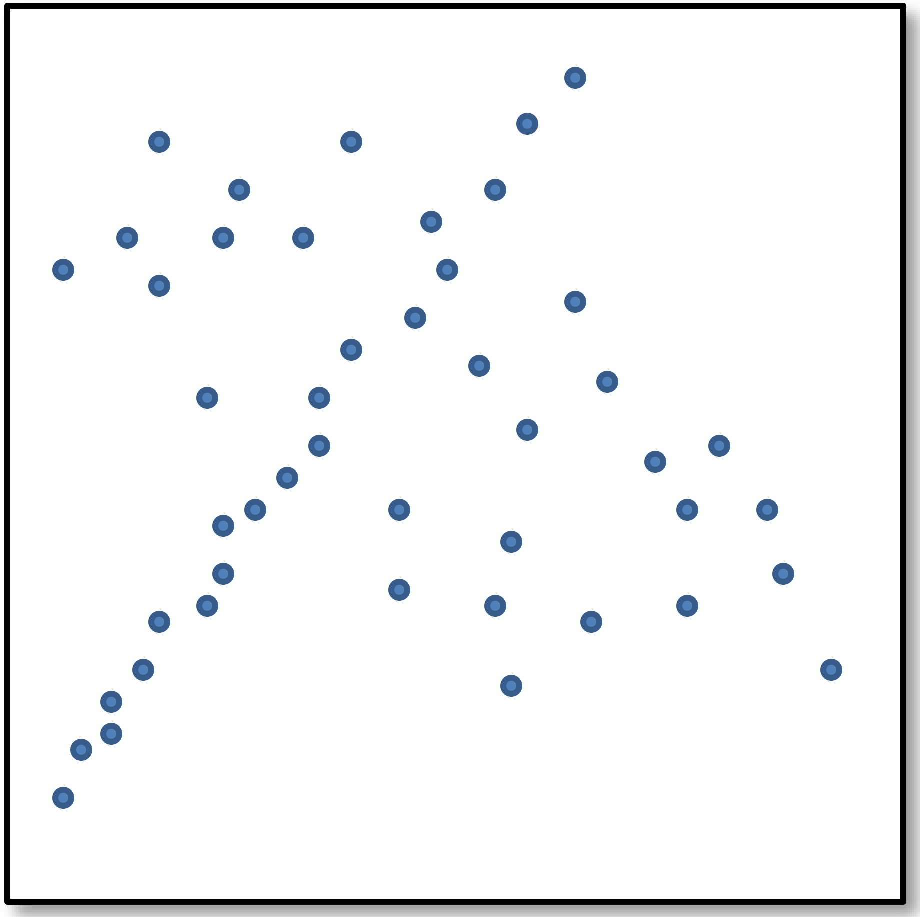
- Suggestions?

Idea

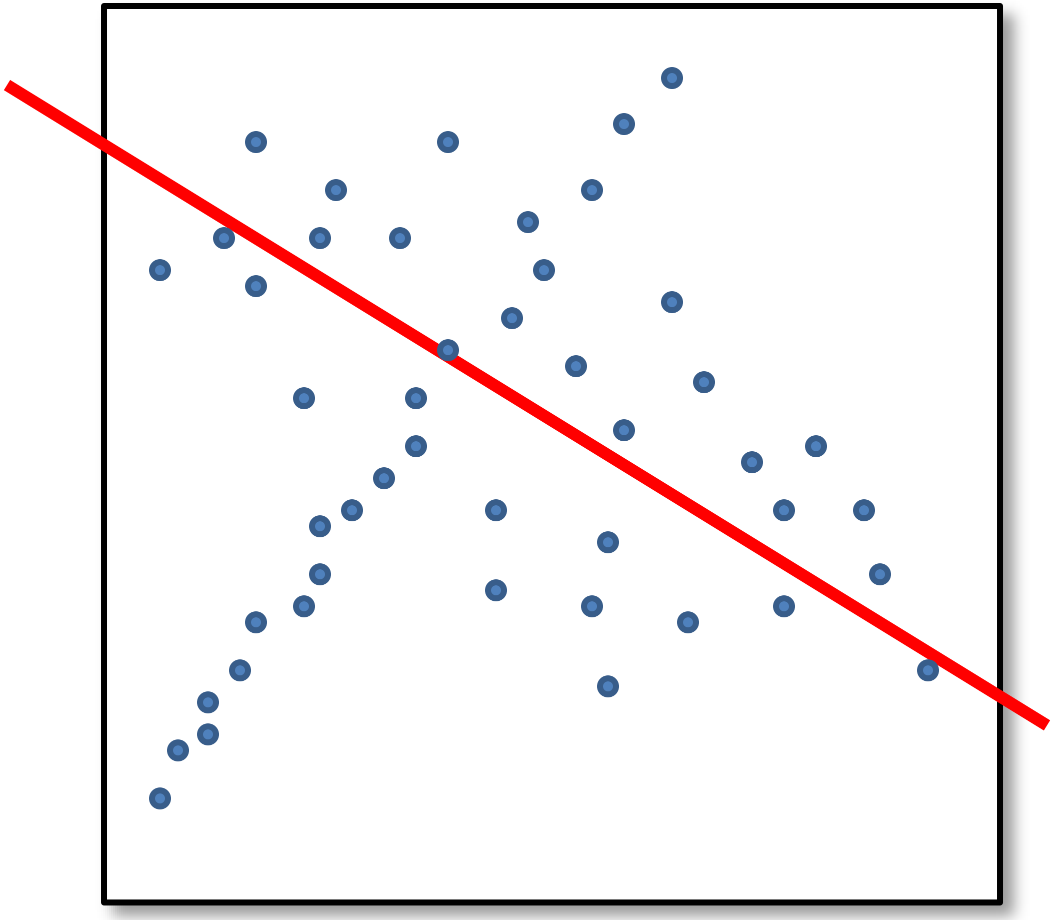
- Given a hypothesized line
- Count the number of points that "agree" with the line
  - "Agree" = within a small distance of the line
  - I.e., the **inliers** to that line

- For all possible lines, select the one with the largest number of inliers

Counting inliers

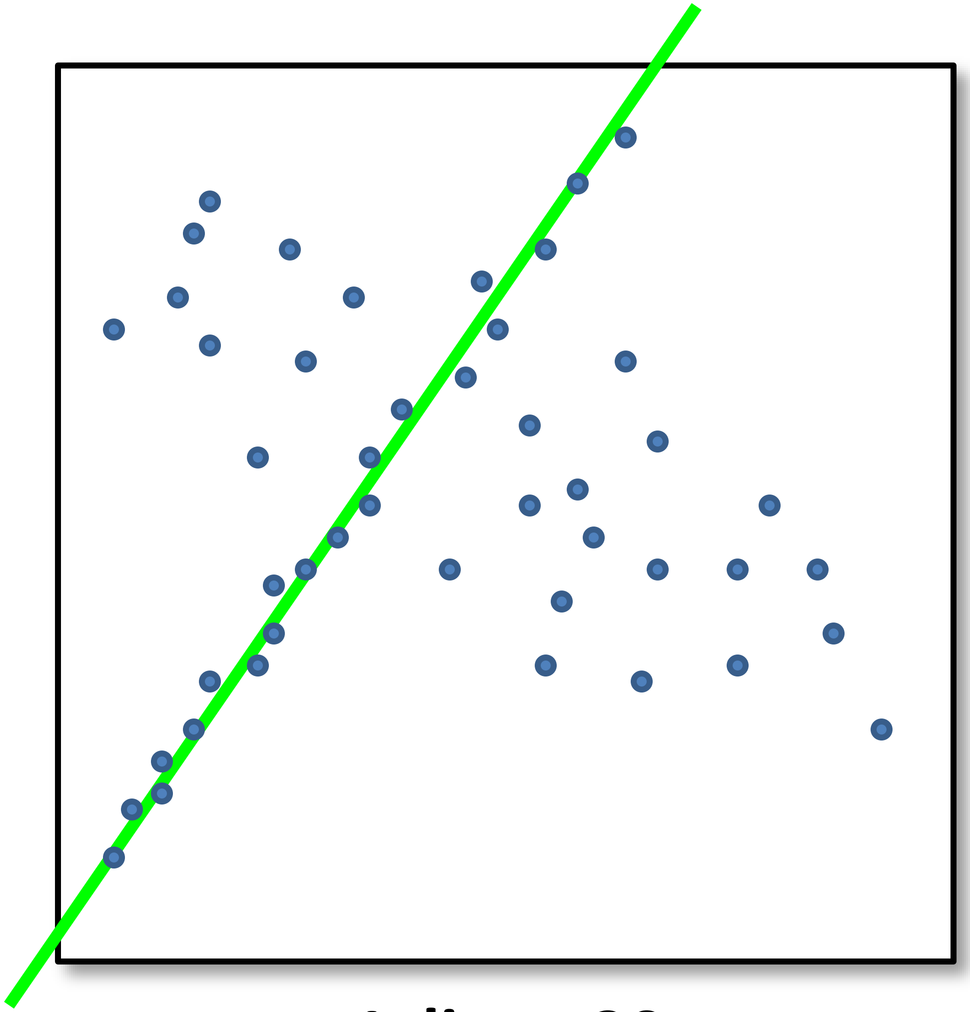


Counting inliers



Inliers: 3

Counting inliers



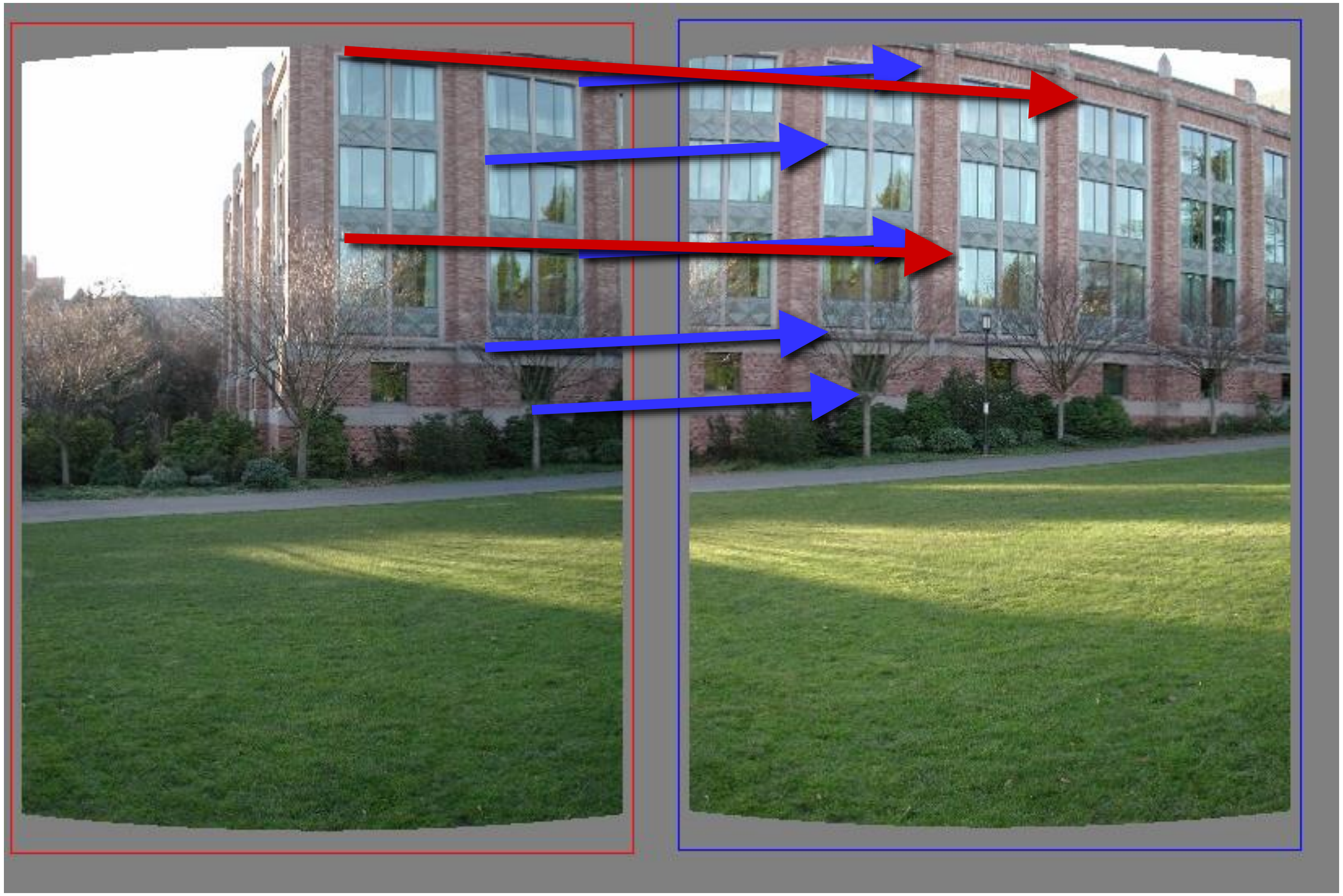
Inliers: 20

How do we find the best line?

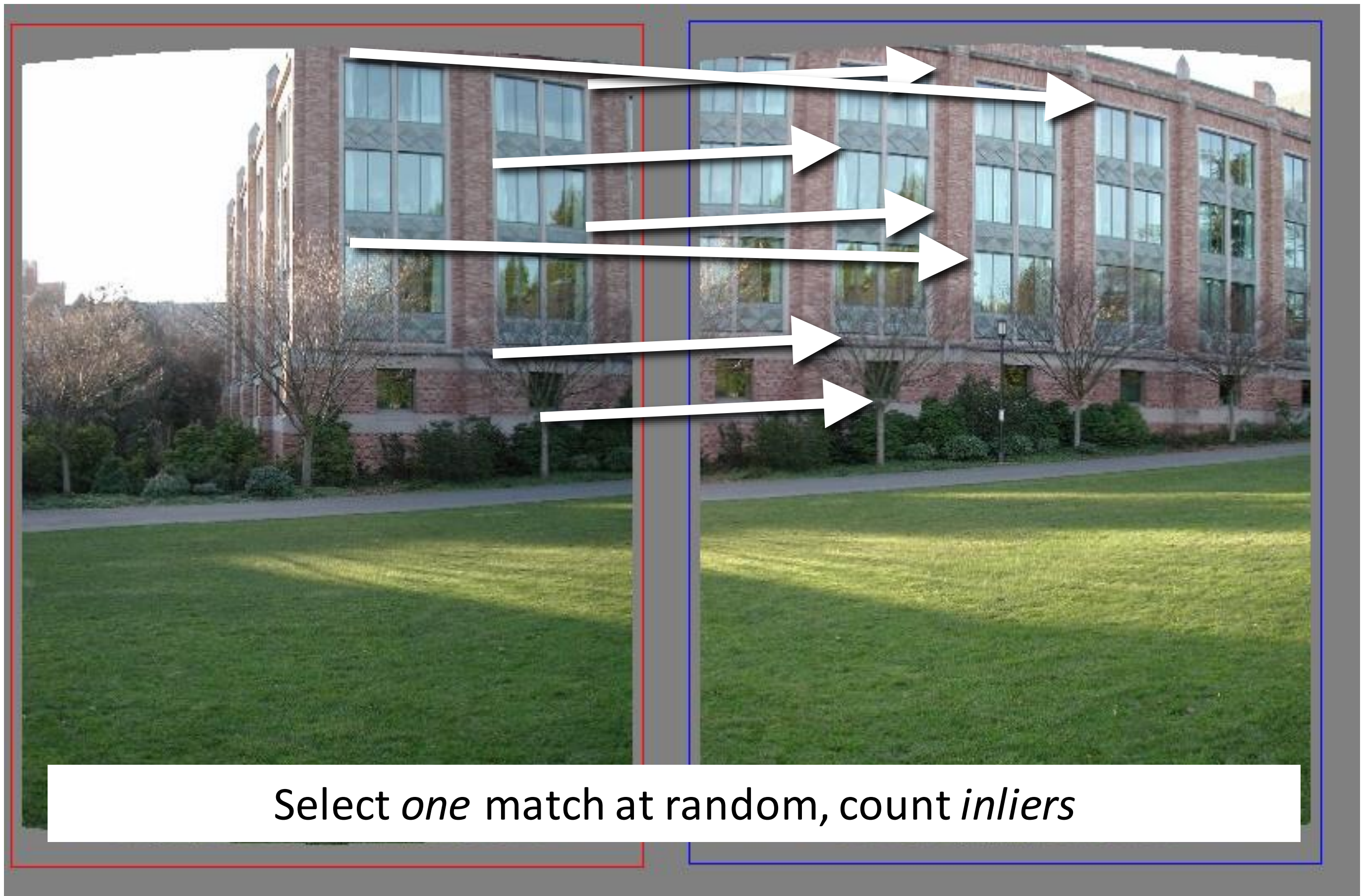
- Unlike least-squares, no simple closed-form solution

- Hypothesize-and-test
  - Try out many lines, keep the best one
  - Which lines?

Translations

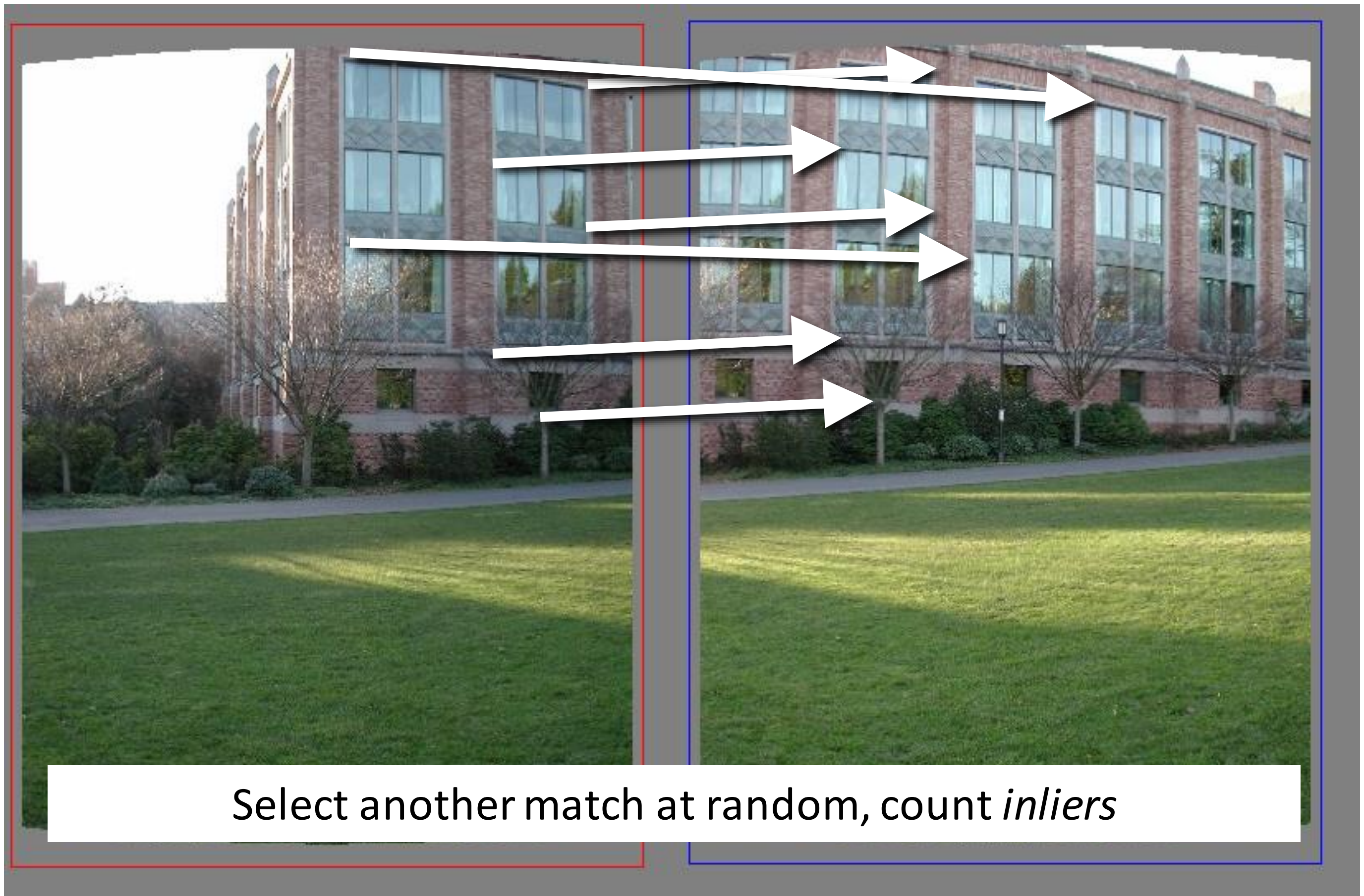


<u>RA</u>ndom <u>SA</u>mple <u>C</u>onsensus



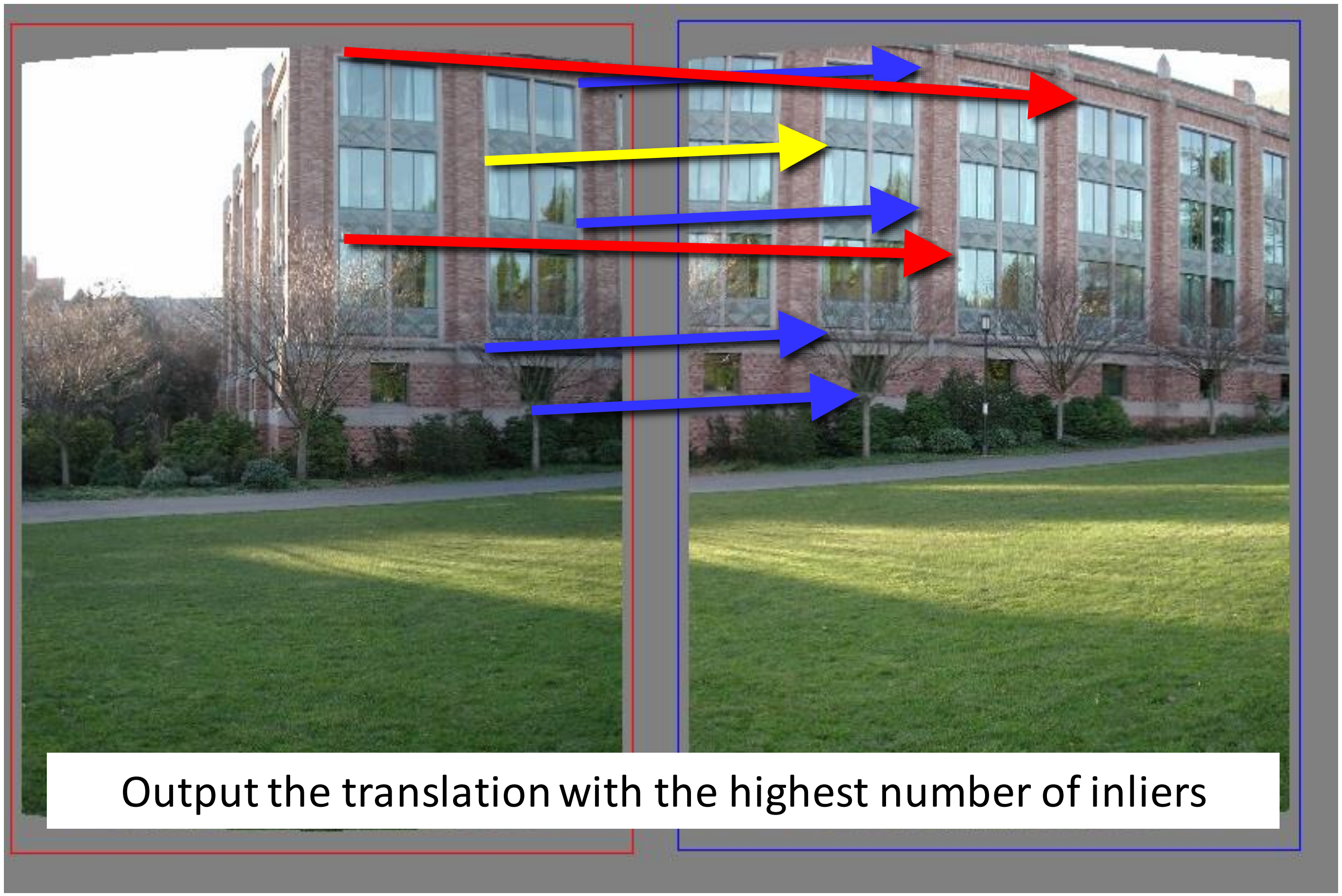
Select *one* match at random, count *inliers*

<u>RA</u>ndom <u>SA</u>mple <u>C</u>onsensus



Select another match at random, count *inliers*

RAndom SAmple Consensus



RANSAC

- Idea:
  - All the inliers will agree with each other on the translation vector; the (hopefully small) number of outliers will (hopefully) disagree with each other
    - RANSAC only has guarantees if there are < 50% outliers

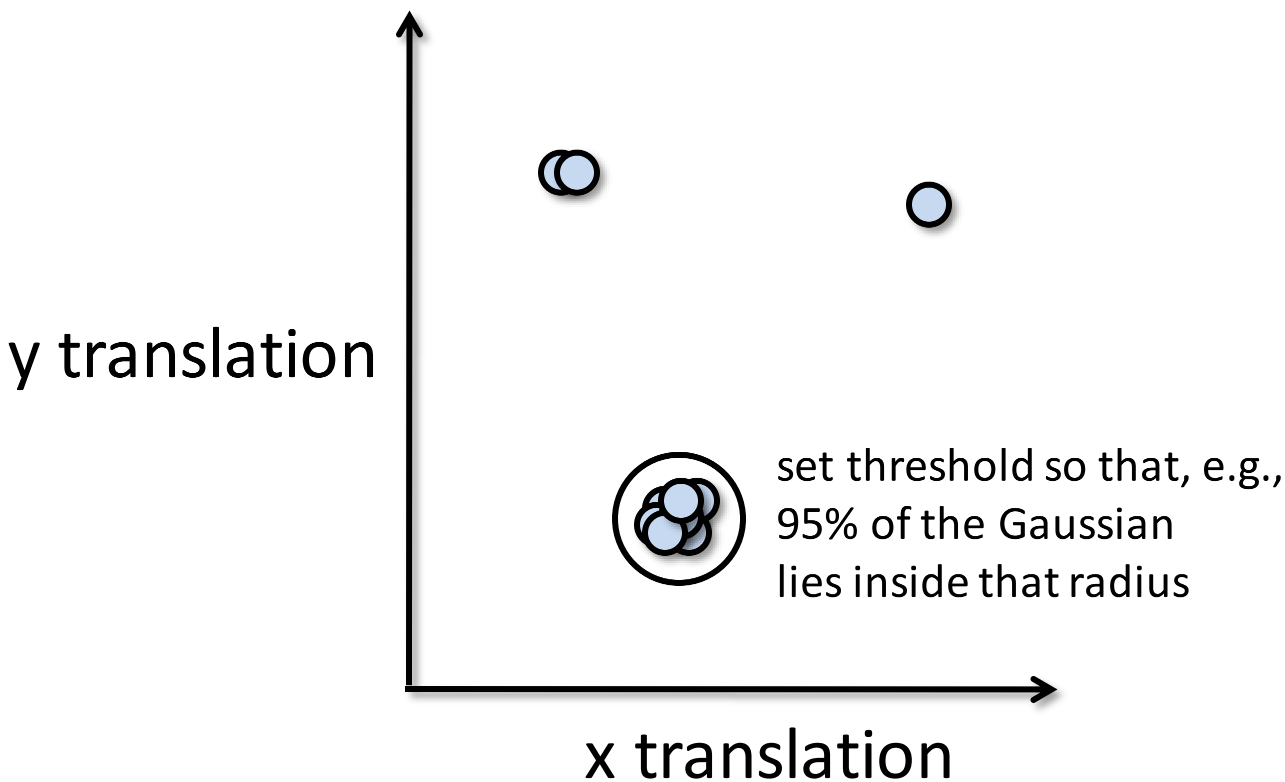
  - "All good matches are alike; every bad match is bad in its own way."

– Tolstoy via Alyosha Efros

RANSAC

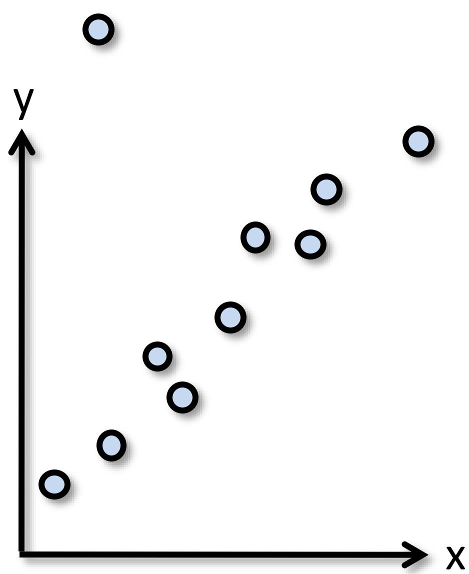
- **Inlier threshold** related to the amount of noise we expect in inliers
  - Often model noise as Gaussian with some standard deviation (e.g., 3 pixels)
- **Number of rounds** related to the percentage of outliers we expect, and the probability of success we'd like to guarantee
  - Suppose there are 20% outliers, and we want to find the correct answer with 99% probability
  - How many rounds do we need?

RANSAC


y translation
set threshold so that, e.g.,
95% of the Gaussian
lies inside that radius
x translation

RANSAC

- Back to linear regression
- How do we generate a hypothesis?



RANSAC

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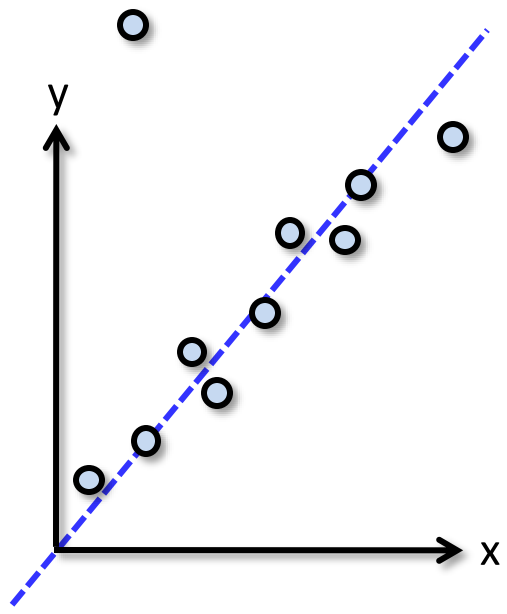


RANSAC

- General version:
  1. Randomly choose *s* samples
     - Typically *s* = minimum sample size that lets you fit a model
  2. Fit a model (e.g., line) to those samples
  3. Count the number of inliers that approximately fit the model
  4. Repeat *N* times
  5. Choose the model that has the largest set of inliers

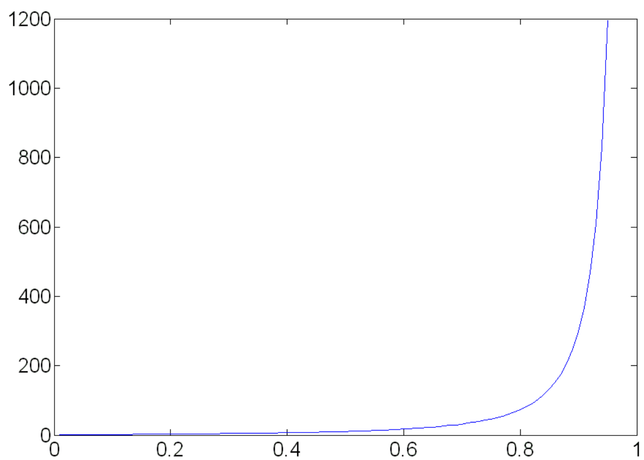
How many rounds?

- If we have to choose *s* samples each time
  - with an outlier ratio *e*
  - and we want the right answer with probability *p*

$$N \geq \frac{\log(1-p)}{\log(1-(1-e)^s)}$$

	proportion of outliers *e*						
s	5%	10%	20%	25%	30%	40%	50%
2	2	3	5	6	7	11	17
3	3	4	7	9	11	19	35
4	3	5	9	13	17	34	72
5	4	6	12	17	26	57	146
6	4	7	16	24	37	97	293
7	4	8	20	33	54	163	588
8	5	9	26	44	78	272	1177

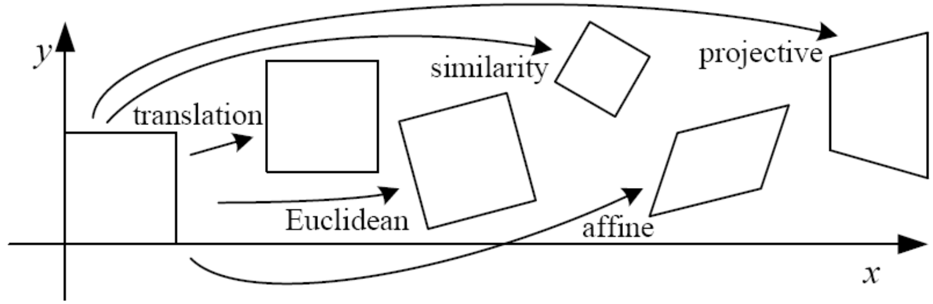
$p = 0.99$



Source: M. Pollefeys

How big is *s*?

- For alignment, depends on the motion model
  - Here, each sample is a correspondence (pair of matching points)

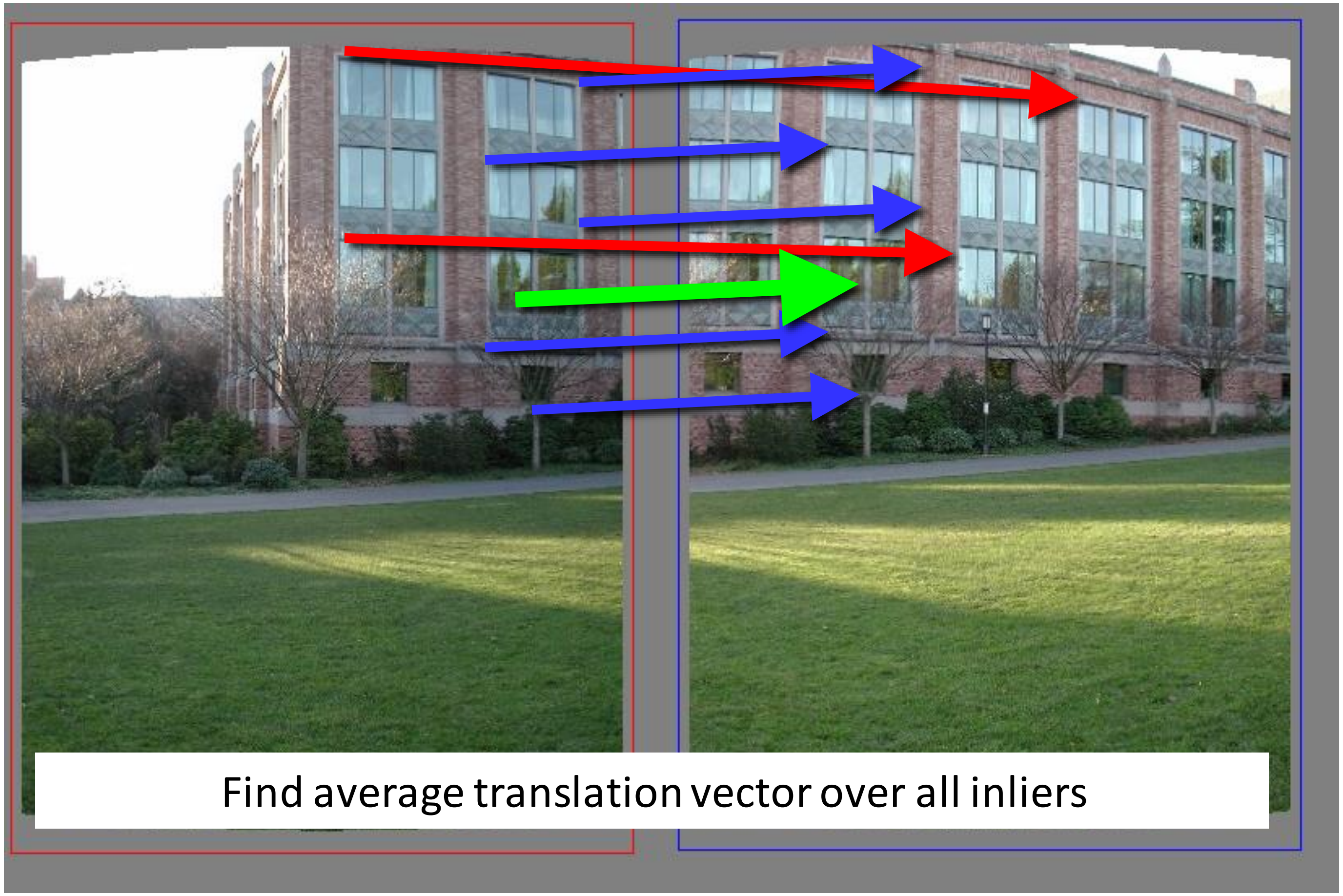


Name	Matrix	# D.O.F.	Preserves:	Icon
translation	$\begin{bmatrix} \boldsymbol{I} \mid \boldsymbol{t} \end{bmatrix}_{2\times 3}$	2	orientation $+\cdots$	
rigid (Euclidean)	$\begin{bmatrix} \boldsymbol{R} \mid \boldsymbol{t} \end{bmatrix}_{2\times 3}$	3	lengths $+\cdots$	
similarity	$\begin{bmatrix} s\boldsymbol{R} \mid \boldsymbol{t} \end{bmatrix}_{2\times 3}$	4	angles $+\cdots$	
affine	$\begin{bmatrix} \boldsymbol{A} \end{bmatrix}_{2\times 3}$	6	parallelism $+\cdots$	
projective	$\begin{bmatrix} \tilde{\boldsymbol{H}} \end{bmatrix}_{3\times 3}$	8	straight lines	

RANSAC pros and cons

- Pros
  - Simple and general
  - Applicable to many different problems
  - Often works well in practice
- Cons
  - Parameters to tune
  - Sometimes too many iterations are required
  - Can fail for extremely low inlier ratios
  - We can often do better than brute-force sampling

Final step: least squares fit



Find average translation vector over all inliers

RANSAC

- An example of a “voting”-based fitting scheme
- Each hypothesis gets voted on by each data point, best hypothesis wins

- There are many other types of voting schemes
  - E.g., Hough transforms…

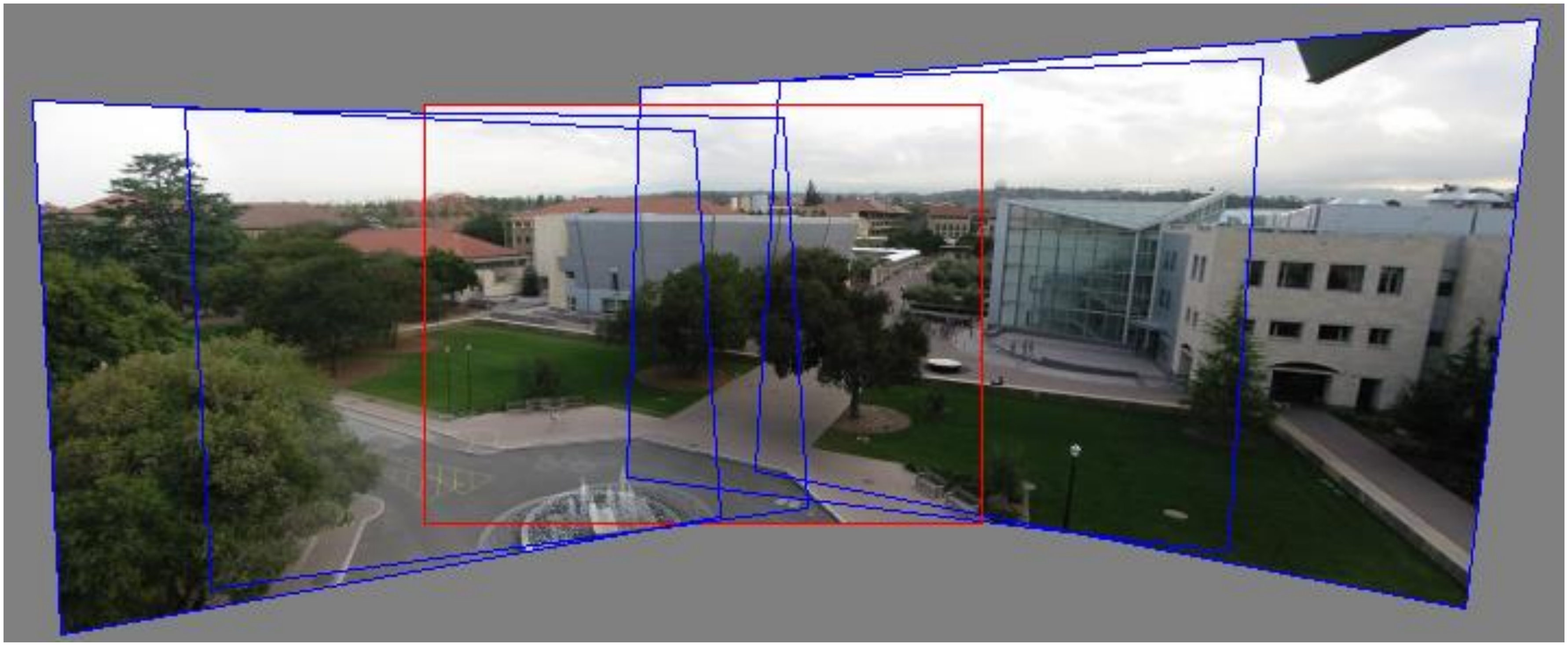
Panoramas

- Now we know how to create panoramas!

- Given two images:
  - Step 1: Detect features
  - Step 2: Match features
  - Step 3: Compute a homography using RANSAC
  - Step 4: Combine the images together (somehow)

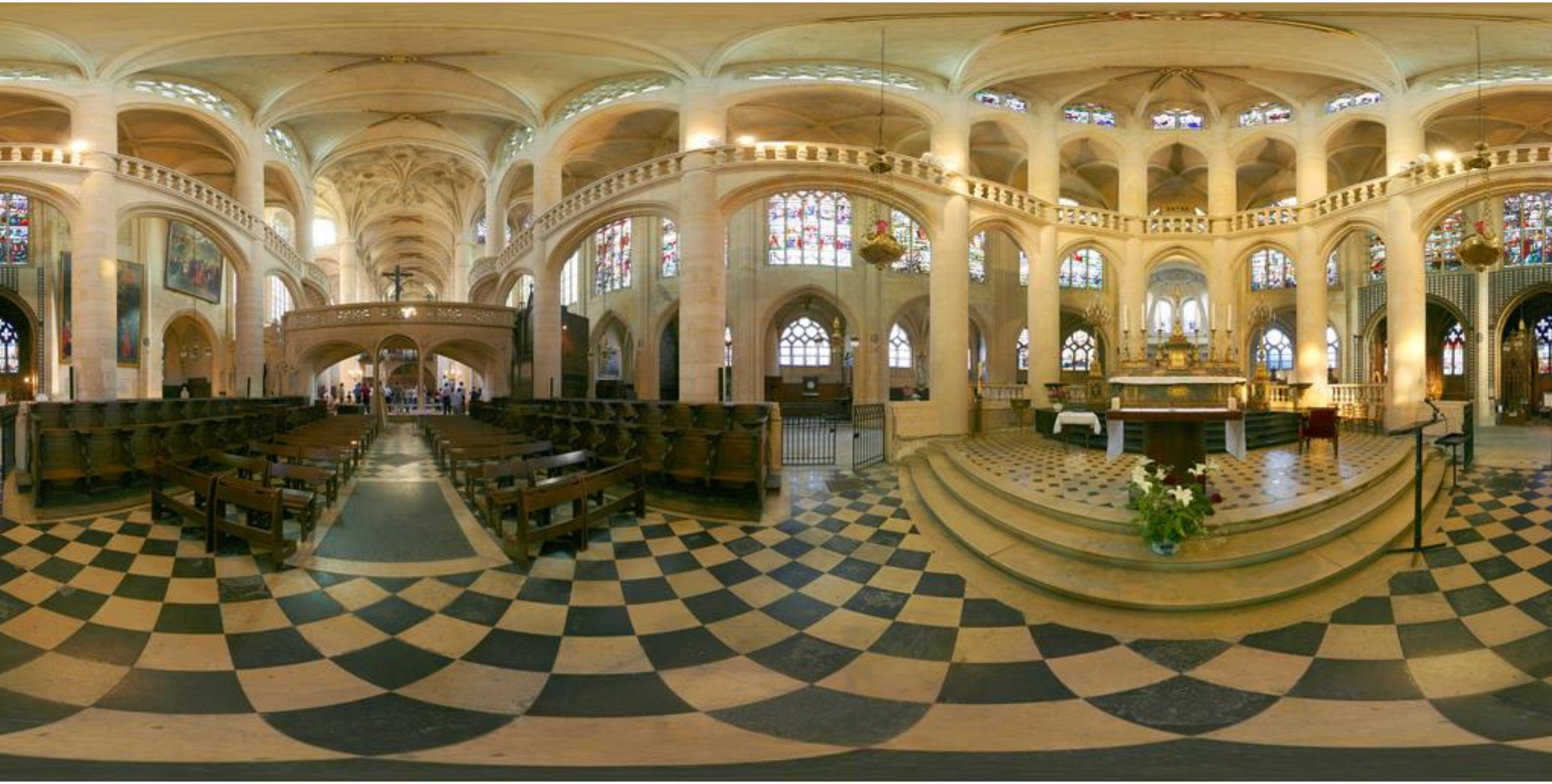
- What if we have more than two images?

Can we use homographies to create a 360 panorama?



- In order to figure this out, we need to learn what a **camera** is

360 panorama



Questions?